

# Exemplar-Based Statistical Model for Semantic Parametric Design of Human Body

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**Abstract**—This paper presents an exemplar-based method to provide intuitive way for users to generate 3D human body shape from semantic parameters. In our approach, human models and their semantic parameters are correlated as a single linear system of equations. When users input a new set of semantic parameters, a new 3D human body will be synthesized from the exemplar human bodies in the database. This approach involves simpler computation compared to non-linear methods while maintaining quality outputs. A semantic parametric design in interactive speed can be implemented easily. Furthermore, a new method is developed to quickly predict whether the parameter values is reasonable or not, with the training models in the human body database. The reconstructed human bodies in this way will all have the same topology (i.e., mesh connectivity), which facilitates the freeform design automation of human-centric products.

**Keywords**— Parametric design, 3D human body, exemplar-based, statistical model, human-centric products.



## 1 INTRODUCTION

**A**UTOMATIC generation of realistic 3D human bodies is an increasingly important topic in many applications such as biometric analysis, computer graphics, and apparel design. Several systems have been proposed that attempt to create general human models from 3D scans. However, the expensive acquisition device – 3D human scanner cannot be afforded by many middle and small enterprises. Therefore, there is a great request from the market to have a parametric design tool for human bodies so that the shape of a 3D human body can be generated from a set of semantic input (e.g., height, chest-girth, waist-girth, hip-girth, inseam-length, etc.).

Past studies have analyzed the body shape coefficients and their variances with various methods. Blanz et al. [1] trained regression functions to correlate them to semantically significant values like weight, body fat content, or pose. Allen et al. [2] utilized parametric freeform mesh design to reconstruct human model from 3D scanner. The parameterization allows them to explore a variety of applications for human body modeling, including: morphing, texture transfer, statistical analysis of shape, model fitting from sparse markers, feature analysis to modify multiple correlated parameters, and transfer of surface detail and animation controls from a template to fitted models. Seo and Magnenat-Thalmann [3] developed a method for generating human bodies given a number of high level semantic constraints and evaluate the accuracy of linear regression based morphing functions. Linear models have been employed in human-centric freeform product design. Scherbaum et al. [4] have concluded from their research concerning face morphing: although non-

linear regression functions are numerically more accurate, the visual difference to the linear counterpart is minimal. Hasler et al. [5] adopted the similar morphing technique as a single linear equation system in the minimum norm sense for human pose modeling. They relate 3D meshes and human body features (e.g. body fat scale, namely weight, body fat percentage, percentage of muscle tissue, water content, and bone weight, etc.) to generate the function of parametric design. Wang [6] adopted a non-linear optimization approach to synthesize 3D human bodies from exemplars while satisfying the input semantic parameters – the computation is very time-consuming.

The above literature review indicates that most past studies concerning human body modeling were focused on animation or human pose generation like [5] and [7]. Little work has addressed the feasibility of this approach on human body modeling for design and manufacturing aspects. The semantic features definition and constraints of 3D human models in design and manufacturing of human-centric products are quite different from those of computer animation. Here, we employ the feature definition given in [6] on the parameterized human bodies, where the semantic features include vertices, curves and patches. Figure 1 gives an example. Moreover, the existing approaches did not offer a mechanism to check the feasibility of input semantic parameters.

In this paper, we provide an intuitive way for the user to generate body shape by appointing a set of semantic values. Human models and the semantic parameters are correlated as a single linear system of equations. This approach involves simpler computation compared to non-linear methods while maintaining quality outputs. By this, a semantic parametric design in interactive speed can be implemented easily. A new method is developed to quickly predict whether the parameter values is reasonable or not, with a set of training models as given in the human model database with 77 female and 83 male subjects.

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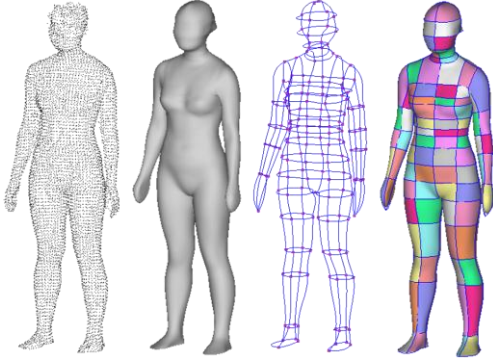


Fig. 1. Parameterization of feature-based human body [6]: (left) point cloud from 3D scan, (middle-left) parameterized human body, (middle-right) feature curves and vertices, and (right) checkerboard to verify feature patches.

## 2 METHODOLOGY

This paper aims to develop a semantic parametric design algorithm which constructs a human model conformed to a set of semantic parameters. Figure 2 shows the overview of proposed method. It mainly consists of four parts. First, a feature model is constructed on each subject from the 3D point cloud by the method in [6]. We then construct a human body database containing training data from the scanned subjects. The next step is to reduce the dimensions in the correlation between body and the parameters by applying Principal Component Analysis (PCA). After the dimensionality reduction, the correlations between scanned models and the semantic parameters can be computed as a simple linear system. A procedure of feasibility check is applied to determine if the parameter values input by the user is reasonable. Finally, new model is constructed in two different ways. The user can specify a model for modification, or we search for the most similar one existing in the training data to work on. Each part of the approach will be explained in detail below.

### 2.1 Feature Model of Human Body

The parametric design method relies on training models to capture 3D body shape with semantic parameters. The training data of this approach is obtained from full body 3D scanning. We employ the feature-based human body parameterization technique developed in the previous work [6] to construct the feature-based human model as well as the semantic parameters for all the 160 subjects. The feature model construction of human body consists of two phases.

- **Feature wireframe construction:** In this step, the key feature points are firstly extracted at underarm, crotch, belly-button, front-neck, back-neck, and bust of a human body. Then, the location of the semantic feature points on the surface of a scanned human body can be determined according to the anthropometrical rules and feature extraction algorithm with fuzzy logic concept [8]. Lastly, the feature points are linked by parametric curves approx-

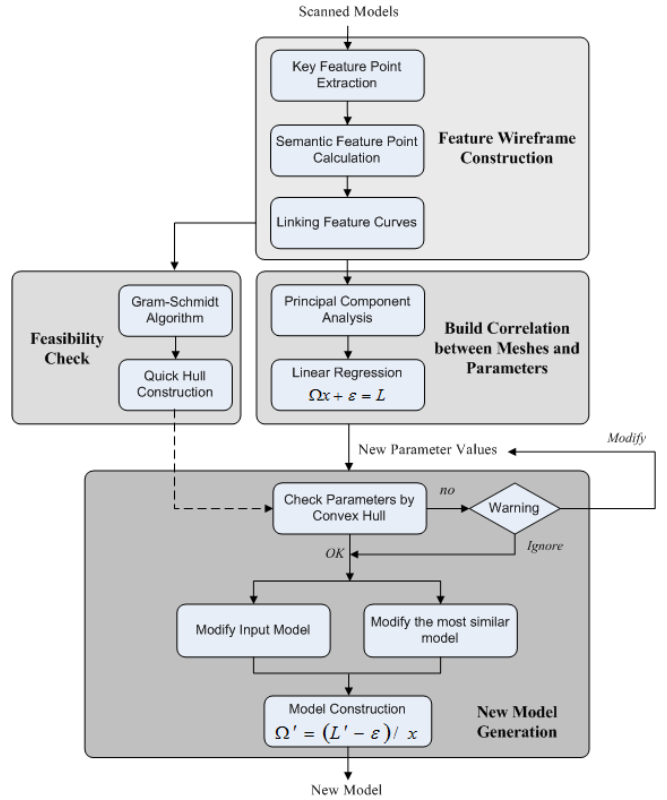


Fig. 2. Overview of the proposed approach.

imating the underline 3D point cloud which indicates the surface of scanned human body.

- **Feature patches generation:** First, Gregory patches are generated to interpolate the feature curves and the cross-tangents defined on them. After that, the surface patches are refined to better capture the geometric details of human bodies. Lastly, a symmetric body can be generated by average the feature model and the mirrored model of itself – this is an optional step only applies to significant asymmetric human bodies.

The resultant feature models are with the consistent mesh connectivity and feature points, curves and patches. Thus, the bijective mapping of points between two human bodies is easily obtained. The synthesis of a new human body can be completed by generating a new mesh with the same connectivity and only positioning the vertices to new locations. The semantic parameters of each training human body can be obtained from the feature points and curves.

### 2.2 Principle Component Analysis

Principal component analysis (PCA) has been used to analyze facial features [2][5]. The main advantage is its lower computational complexity by discarding relationships of low variance. The full dataset does not need to be retained to approximate the original examples.

Assume there are  $m$  scanned models serves as exemplars, we list them in a matrix

$$A = [a_1 \ a_2 \ \dots \ a_m]_{3n \times m}$$

with  $a_i$  being a  $3n \times 1$  vector with  $n$  vertices from the mesh

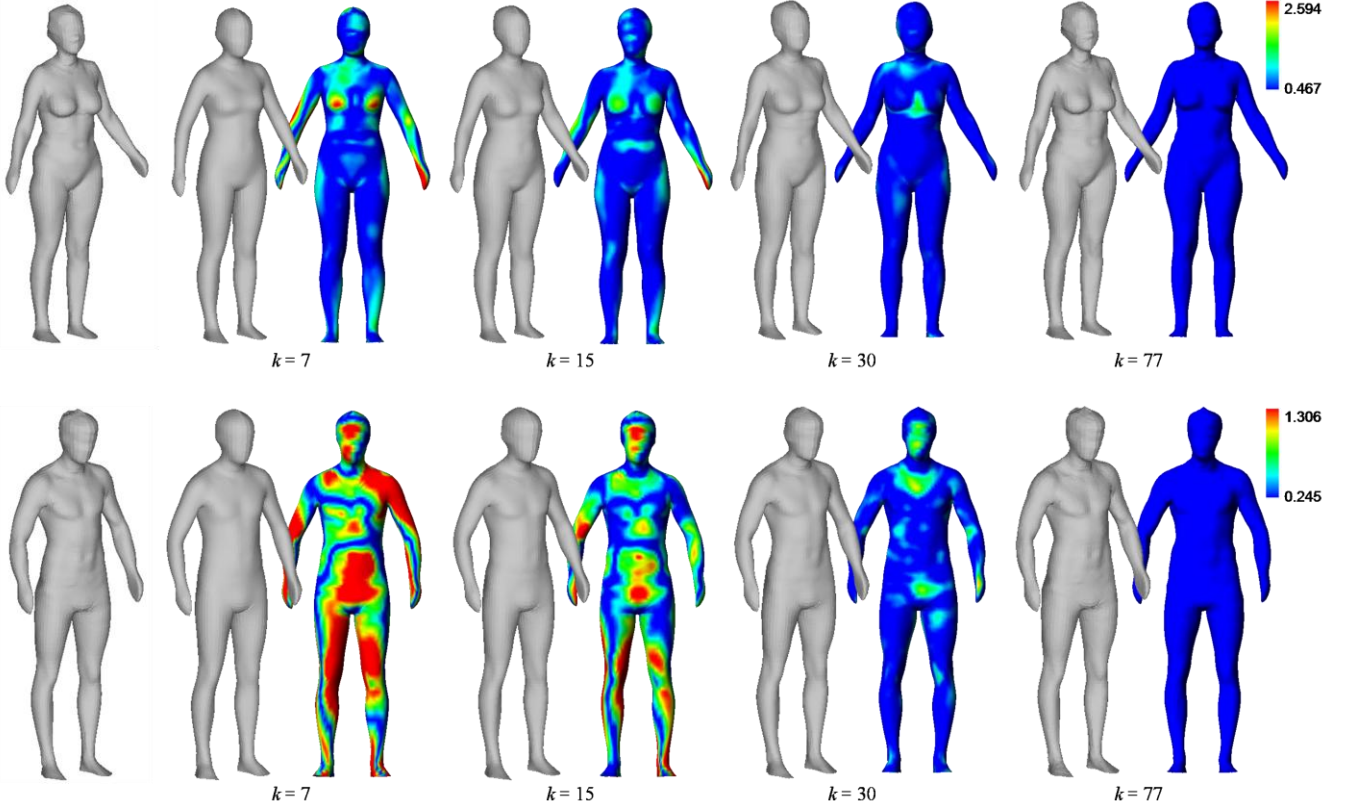


Fig.3. The reconstructed human bodies using different number of PC coefficients (i.e., different  $k$ ) – using more coefficients can get better results. The color map is generated by the publicly available PolyMeCo [11] to visualize the geometric error between the reconstructed human model and the original model. As there are 83 male subjects, when  $k=77$ , the reconstructed male body is still an approximation.

surface of the  $i$ th feature model in our dataset. Letting

$$\bar{a} = \frac{1}{m} \sum_{i=1}^m a_i,$$

we can have

$$\bar{A} = [(a_1 - \bar{a}) \ (a_2 - \bar{a}) \ \dots \ (a_m - \bar{a})]_{3n \times m}.$$

The covariance of  $\bar{A}$  is  $C = \bar{A}(\bar{A})^T$ , whose dimension is  $3n \times 3n$ . As  $3n \gg m$ , we instead compute the transpose of its covariance,  $D = (\bar{A})^T \bar{A}$  (ref. [9]). Apply Eigenvalue decomposition on it as

$$Dx = \lambda x,$$

we can obtain  $m$  eigenvectors,  $x_j$ , which is  $m \times 1$ . By  $x_j$ , we can determine the  $j$ th eigenvector of  $C$  as

$$y_j = \bar{A}x_j,$$

where  $y_j$  is a  $3n \times 1$  vector. The normalized eigenvectors  $\hat{y}_j = y_j / \|y_j\|$  ( $j=1, \dots, m$ ) are the principal vectors of  $\bar{A}$ , where each is associated with a variance  $\sigma_j$ . The vectors are sorted so that

$$\sigma_1^2 \geq \sigma_2^2 \geq \dots \geq \sigma_m^2.$$

The largest variance means the corresponding vector  $y_j$  has the most dominant effect when modifying the model. We keep the first  $k$  principal components according to the percentage of the total variance explained  $r$  by each principal component.

$$r = \frac{\lambda_1 + \lambda_2 + \dots + \lambda_k}{\lambda_1 + \lambda_2 + \dots + \lambda_1 + \dots + \lambda_m}$$

The scanned models serving as training data set can be

projected onto  $k$ -dimensional points by (ref.[9])

$$b_i = \begin{bmatrix} \hat{y}_1^T \\ \hat{y}_2^T \\ \vdots \\ \hat{y}_k^T \end{bmatrix} (a_i - \bar{a}).$$

Thus, we map  $A_{3n \times m}$  into a reduced matrix  $B_{k \times m} = [b_i]$  ( $k \ll 3n$ ) spanning the linear space of exemplar human bodies, named as the *reduced exemplar matrix*.

Although the value of  $k$  can be chosen by experiences, e.g., let  $k=0.95$ , we can also determine it in a better controlled way according to a user given geometric error tolerance,  $\varepsilon$ . After mapping a scanned model  $a_i$  into a  $k$ -dimensional point  $b_i$ , an approximated human model  $\tilde{a}_i$  can be synthesized from the  $k$  scalars in  $b_i$  by

$$\tilde{a}_i = [\hat{y}_1 \ \hat{y}_2 \ \dots \ \hat{y}_k] b_i + \bar{a}.$$

In principle, choosing greater value for  $k$  will make the  $L^2$  norm,

$$L^2(b_j) = \|\tilde{a}_i - a_i\|^2,$$

between  $\tilde{a}_i$  and  $a_i$  smaller. Figure 3 shows the reconstructed models from 7, 15, 30 and 77 coefficients respectively and the geometric error between them and the original models. We can start from an initial guess  $k$  to see if the  $L^2$  norms on all  $\tilde{a}_i$ s are smaller than  $\varepsilon$ . If not, we will increase  $k$  by one and check again. Repeating this step, a minimal value of  $k$  satisfying the given geometric error tolerance can be determined.



Fig.4. On increasing the bust-girth of a model from 91cm (left) to 99cm (right) – feasible human body can be reconstructed. The computation employs 15 PC coefficients.

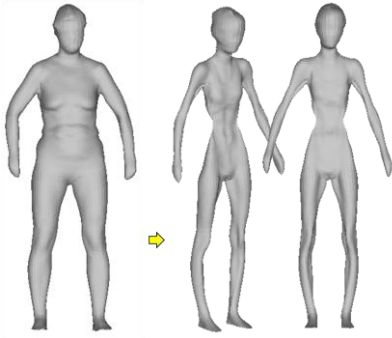


Fig.5. On decreasing the waist-girth of the model from 80cm (left) to 30cm (right) – infeasible models are generated. The computation employs 15 PC coefficients as well.

### 2.3 Correlation with Semantic Parameters

The PCA method helps characterize the space of human body variation, but it does not provide the correlation between the body shape and the semantic features. Here we show how to relate several variables simultaneously by learning the relationships between the body parameters and the PCA weights. Such relationships serve as the key for synthesizing a desired model from a set of input semantic parameters.

Suppose we have  $p$  semantic parameters of each scanned model, listing the parameters for all  $m$  examples forms a semantic parameter matrix

$$L = [l_1 \quad l_2 \quad \cdots \quad l_m]_{p \times m}$$

with  $l_i$  a  $p \times 1$  vector. The correlation between  $L$  and the reduced exemplar matrix  $B$  can be represented by a system of linear equations. More specifically, we assume

$$Rb_i + \mu = l_i \quad (i=1, \dots, m)$$

where  $R_{p \times k}$  is the relation matrix and the vector  $\mu_{p \times 1}$  is a corresponding residual. If  $m > k+1$ , the value of  $R$  and  $\mu$  can be determined through a least-square solution.

Given a new set of semantic parameters,  $l_{new}$ , the corresponding coefficient in the reduced linear space  $B$  can be computed by

$$b_{new} = (l_{new} - \mu)R^T.$$

Then,

$$a_{new} = [\hat{y}_1 \quad \hat{y}_2 \quad \cdots \quad \hat{y}_k] b_{new} + \bar{a}.$$

Note that, if the value of  $p$  is not changed, we can pre-compute  $R$  and  $\mu$ , and the computations in the whole regression and reconstruction procedure is just linear substitution which can be completed in an interactive speed.

Figure 4 shows an example with the model's bust size increased from 91cm to 99cm. However, the generalization derived from the linear system is constrained by the exemplars used. Given that most of the scanned models are of normal parameter ranges, the new model constructed with parameter values out of the ranges can be problematic. For example (see Fig. 5), it is not adequate to modify the waist size from 80cm to 30cm. Unreasonable meshes apparently occur in the output model (Fig. 5). The values out of modifiable ranges may easily cause twist in the output model. Certainly better generalization performance can be achieved by adding more extreme exemplars.

### 2.4 Feasibility Check

To overcome the above problem, we propose a method to estimate the quality of the new model produced by a set of parameter values input by the user. It determines whether the resultant model is of a good quality by considering the parameter ranges in the training data. The method first computes the convex hull corresponding to the linear system in the parameter space. If the new feature vector is in the convex hull, the outcome should be reasonable. On the contrary, the new model is likely to become problematic when the vector is far from the convex hull region. The convex hull of a set of points is the smallest convex polyhedron that contains the points. The convex hull is a fundamental construction for mathematics and computational geometry. The feasibility check with the convex hull approach is described as follows.

We regard the semantic parameter matrix as a set of  $m$  points in a  $p$ -dimensional coordinate system. To compute the convex-hull, the coordinates of a point must independent to each other. However, this is not the case. Usually, the semantic parameters of human bodies are not independent, e.g., a taller model often has a longer inseam. Therefore, a normalization process is needed to establish the orthonormal basis. Gram-Schmidt algorithm [12] is a common method to construct an orthogonal basis for an arbitrary dimensional space. Given a set of bases  $\{u_1, u_2, \dots, u_n\}$  spanning an  $n$ -dimensional inner product space  $U$ . The Gram-Schmidt algorithm constructs a new set of orthogonal bases  $V = \{v_1, v_2, \dots, v_n\}$ , which spans the same  $n$ -dimensional space as  $U$ . By defining the projection operator, that projects the vector  $v$  orthogonally onto the vector  $u$ , as

$$proj_v u = \frac{\langle v, u \rangle}{\langle v, v \rangle} v,$$

where  $\langle v, u \rangle$  denotes the inner product of  $v$  and  $u$ . The Gram-Schmidt process then works as follows:

$$v_1 = u_1,$$

$$v_2 = u_2 - proj_{v_1} u_2 = u_2 - \frac{\langle v_1, u_2 \rangle}{\|v_1\|^2} v_1,$$

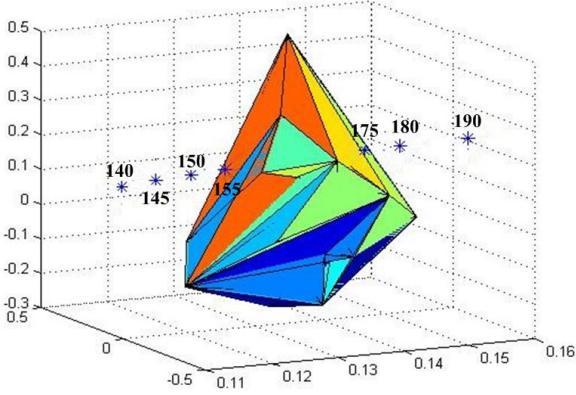


Fig.6. Parameterization of feature-based human body [6]: (left) point cloud from 3D scan, (middle-left) parameterized human body, (middle-right) feature curves and vertices, and (right) checkerboard to verify feature patches.

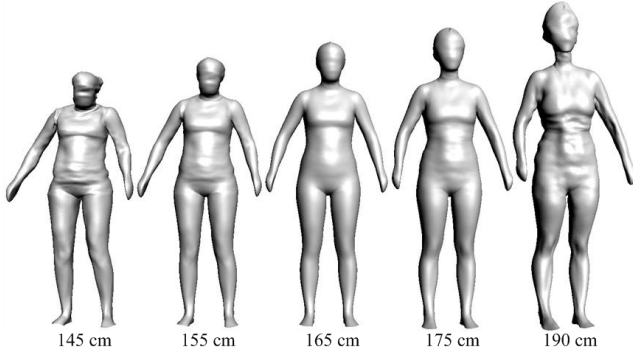


Fig.7. Parameterization of feature-based human body [6]: (left) point cloud from 3D scan, (middle-left) parameterized human body, (middle-right) feature curves and vertices, and (right) checkerboard to verify feature patches.

$$v_3 = u_3 - \text{proj}_{v_1} u_3 - \text{proj}_{v_2} u_3 = u_3 - \frac{\langle v_1, u_3 \rangle}{\|v_1\|^2} v_1 - \frac{\langle v_2, u_3 \rangle}{\|v_2\|^2} v_2, \\ \vdots, \\ v_n = u_n - \sum_{j=1}^{n-1} \text{proj}_{v_j} u_n.$$

The sequence  $v_1, v_2, \dots, v_n$  is the required system of orthogonal vectors and the normalized vectors  $e_1, e_2, \dots, e_n$  form an orthonormal set by  $e_i = v_i / \|v_i\|$ .

In our case, after calculating the orthonormal bases  $\{e_1, e_2, \dots, e_p\}$  from  $L$ , the parameters  $l_i$  of each subject  $i$  are projected onto the new bases to become  $l_i^e$ . Then, the convex hull of  $m$  points:  $l_i^e$  ( $i=1, \dots, m$ ) is constructed by the *Quick-Hull* algorithm (ref. [13]). The convex hull constructed with the projected semantic parameters,  $l_i^e$ , defines the feasible area of the linear system. If a new vector is outside and far from the convex hull, the resultant model is likely to be invalid. Fig. 6 shows an example for a gradual change of parameter values in a 3-dimensional space and comparing with the convex hull. The star point indicates the new parameter. For explanation simplification, we only select 3 semantic parameters: height, bust-girth, and waist-girth. In this case we are going to modify

the height of a female model from the original height 168cm to different heights. From Fig.7, it is easy to find that only the models with height 155cm, 165cm and 175cm are reasonable. For the corresponding points in the projected parameter space (see Fig. 6), the positions with respect to 155cm and 175cm are on the boundary of convex hull, and the position with respect to 165cm is inside.

Generally, we can use the convex hull  $E$  of the projected  $m$  points:  $l_i^e$  ( $i=1, \dots, m$ ), to check the feasibility of input parameters. For a given  $l_{new}^e$ , it is firstly projected to become  $l_{new}^e$ . If  $l_{new}^e$  is inside the convex hull  $E$ , the given parameters in  $l_{new}^e$  are feasible. Otherwise, we either reject the input, or project  $l_{new}^e$  onto the closest point on the surface of the convex-hull  $E$  to compute the reconstructed model.

### 3 EXPERIMENTAL RESULTS

This section discusses the experimental results under different test conditions. The results demonstrate the efficacy of the proposed method. In section 3.1, we discuss the effect of selecting different principle components on the reconstructed human models. Section 3.2 shows the test results when the size of training data is small. The purpose is to show the stability of the proposed linear model. Finally, we intentionally add a noise model to the training data. The robustness of our method is thus validated.

#### 3.1 Selection of Principal Components

Figure 8 and 9 list the shape variation on first seven principal components from our training data set. It is important to choose a proper threshold in the PCA step that balances between the degree of data variance it produces and the system complexity. We have to keep enough principal components to capture the variance in the training data. Insufficient principal components may result in inaccurate reconstructed models as already been analyzed in previous section. However, retaining more principal components is not always advantageous. The solution process may require excessive computational load imposed by higher system complexity. Furthermore, too many components may capture unnecessary details that contain noise and thus weaken the effectiveness of the linear regression model.

We select 76 female models as the training data in this example. Suppose we are going to apply the parametric design on a human model, which has been shown in Fig.5 previously. Four semantic parameters (Height, Bust, Waist, and Inseam) are of our concern in this case. We intend to change the bust size of the model from 91.1831cm to 100cm while keeping the other parameters fixed. Figure 10 shows the cumulative percentage versus the number of the principal components retained. As shown in Fig. 10, we first take seven principal components according to the general standard 80% [9] to generate a synthesized female model from the exemplars. The resultant model looks good (see Fig. 11), but detailed investigation shows one problem. Although the bust size of the result - 99.81cm is satisfactory, the waist size is not properly maintained, i.e. 85.69cm vs. 80.4519cm of the

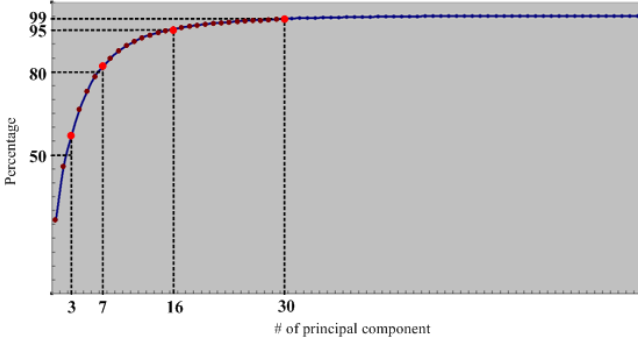


Fig.10. Cumulative percentage of variance vs. the number of principal components.



Fig.12. An example of parametric design of human body: to build a model with Height = 174cm, Bust = 93cm, and Waist = 80cm.

original. We thus test out different numbers of principal components to find an optimal threshold. Figure 11 shows the corresponding results. The height in the model produced by 50% variance (with only three principal components) is not maintained (164.23 cm vs. 168.397 cm). For the high variance percentages 95% and 99%, all the parameters of the new models are acceptable. The component numbers are 16 and 30, respectively. However, when increasing from 95% to 99%, only ~5% the memory and computation cost has been almost doubled. Therefore, we usually choose 95% as a trade-off between the accuracy and the efficiency.

With an optimal selection of principal components, we are now able to use the relation  $b_{new} = (l_{new} - \mu)R^T$  to do parametric design of 3D human body. For example, the user specifies the semantic parameters: Height = 174cm, Bust = 93cm, and Waist = 80cm. A new feature vector  $l_{new}$  is constructed based on the input. Next, a model (shown in Fig.12) with a similar parameters (Height = 175.343cm, Bust = 95.788cm, Waist = 78.9447cm, and Inseam = 79.1214cm) is selected. Before applying the relation to obtain  $b_{new}$  we determine if the new parameters are reasonable by the proposed Convex Hull method. The projected point  $l_{new}^e$  is located in the convex hull, so we expect the customized model is of a good quality. We then apply the linear model to generate a new model (see Fig. 12). The parameters of the resultant model are Height = 173.01cm, Bust = 90.68cm, Waist = 79.02cm, and Inseam = 80.22cm. The reconstructed human body is satisfactory

TABLE 1  
FIVE MODELS WITH EXTREME VALUES IN FOUR PARAMETERS

	Model 1	Model 2	Model 3	Model 4	Model 5
Height	<u>200.58</u>	159.32	177.86	187.53	178.43
Chest	99.34	90.29	91.43	<u>112.53</u>	<u>80.65</u>
Waist	81.38	77.82	<u>68.37</u>	<u>112.40</u>	75.98
Inseam	<u>94.86</u>	<u>65.91</u>	82.99	87.77	81.19

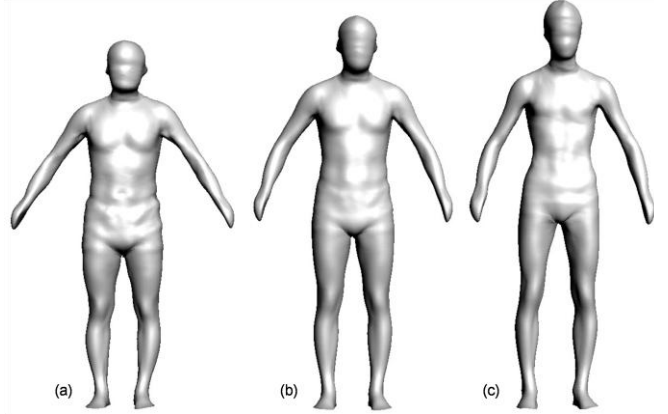


Fig.13. The example of parametric design when with only five exemplars: (a) the original model, (b) by heightening from 159.32cm to 170cm, and (c) by thinning the waist from 77.82cm to 68cm.

both visually and parametrically.

### 3.2 Stability Test

This example is conducted to show the stability of our method with a small set of exemplars. Only 5 male models are selected from the database. For preserving data variation, these models contain the extremes of four parameters: Height, Chest, Waist, and Inseam (see Table 1). Model 1 is the tallest and has the longest inseam; Model 2 is the shortest and has the shortest inseam; Model 3 has the smallest waist size; Model 4 has the largest chest and waist; Model 5 has the smallest chest.

Seven principal components are remained (i.e., >95% total variance is kept). Here, we only allow one single parameter to vary due to a low number of training models. Figure 13 shows the tests. First, we try to enlarge the height of Model 2 from 159.32cm to 170cm. The height of the reconstructed model (see the middle of Fig.13) is 169.98cm – very close to the target. The other parameters change in proportion to the height in this case, especially Inseam. Secondly, we change to another parameter – waist to conduct the parametric design. The waist girth is expected to be reduced from 77.82cm to 68cm. The resultant model (shown in the right of Fig.13) has the waist-girth 66.3cm. These two tests demonstrate a high stability of our algorithm under the condition of fewer training data. The linear regression method works quite stably under such circumstance. This property is highly advantageous when with data shortage. Certainly more training models improve the quality and accuracy in our method.

### 3.3 Robustness Test

Robustness is another desired property in parametric design of human models. A robustness test is thus con-

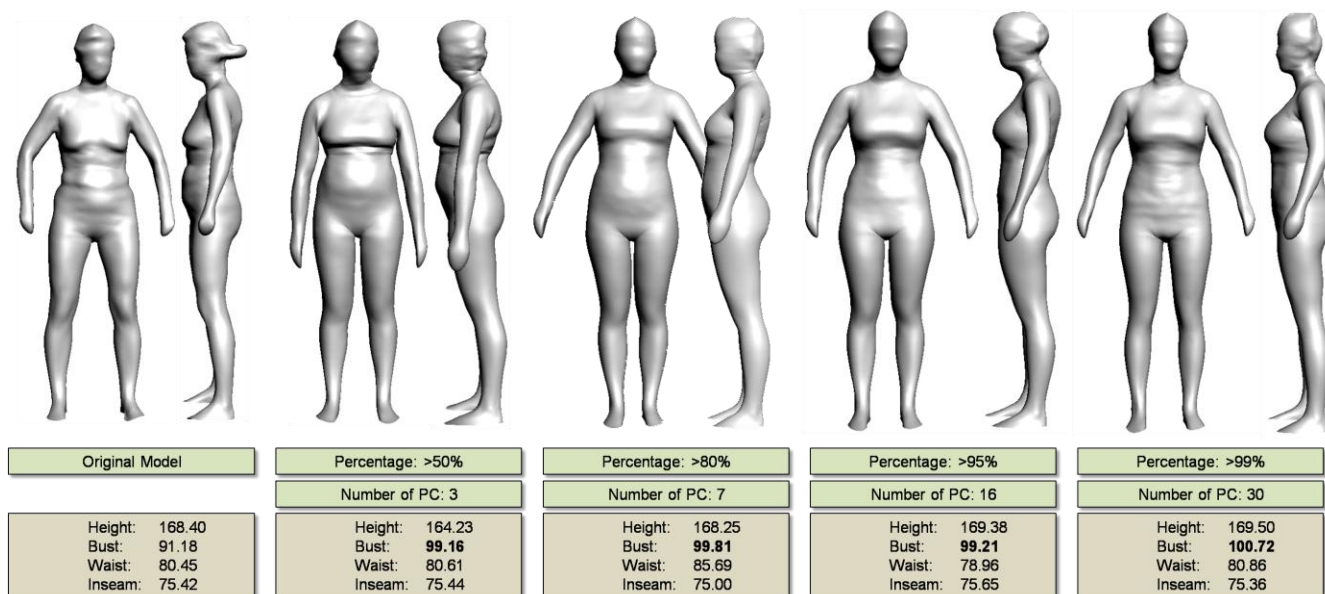


Fig.11. The results of retaining different number of principal components according to the percentage of total variance when modifying the bust size of original model from 91.18cm to 100cm – the other three dimensions are expected to not change.

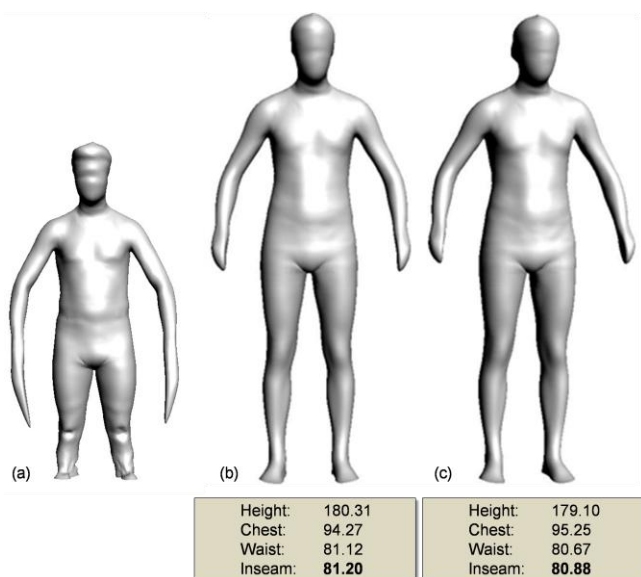


Fig.14. Robustness test: (a) the noisy model with an abnormal ratio of inseam to the sleeve length, (b) the reconstructed model with the noisy training data – target inseam at 80cm, and (c) the reconstruction without noise.

ducted to verify that on our method. We intentionally add an invalid model as a noise into the five training models in the previous section. The noise model (see Fig. 14(a)) has an abnormal ratio of inseam to the sleeve length. A design method of high robustness is expected to tolerate the noise.

Now there are six models in the test with Inseam as the only parameter to vary. We change the inseam of Model 2 (shown in Fig.13(a)) from 65.911cm to 80cm. The result (Fig. 14(b)) looks very similar to the model produced without noise in the training data (Fig. 14(c)). Therefore, it is easy to find that the linear regression model tends to average out the noise.

#### 4 CONCLUSION AND DISCUSSION

Modeling of realistic 3D human bodies plays an essential role in many applications like computer animation, biomedical analysis, human-centric product development, and fashion design. The functional requirements and constraints of human body modeling vary across different applications. Most past studies were focused on the model construction for computer animation or human pose generation. Less work concerned parametric design of human body for the design and manufacturing of human-centric products. In this paper, we developed a novel method for parametric design of human models from semantic input. The design mechanism was driven by a statistical model constructed from a set of body shape exemplars. Feature-based human models were used to explicitly define the control parameters and assure the unity of topology of each model. The correlations between the semantic parameters and 3D meshes of a human model were characterized as a statistical linear system. Such a linear approach requires simpler computation compared to nonlinear methods. Our method conducted Principal Component Analysis (PCA) for reducing the complexity of the linear system while maintaining a good capability of shape preserving. We also developed a technique based on convex hull calculation to predict whether the parameter values given by the user produce a satisfactory model. The test results in different conditions demonstrate the practicality of this work. The proposed method worked well with few training data. It could also tolerate noisy data, showing a high robustness. We expect that the parametric design method of human models greatly improves design automation of human-centric products as

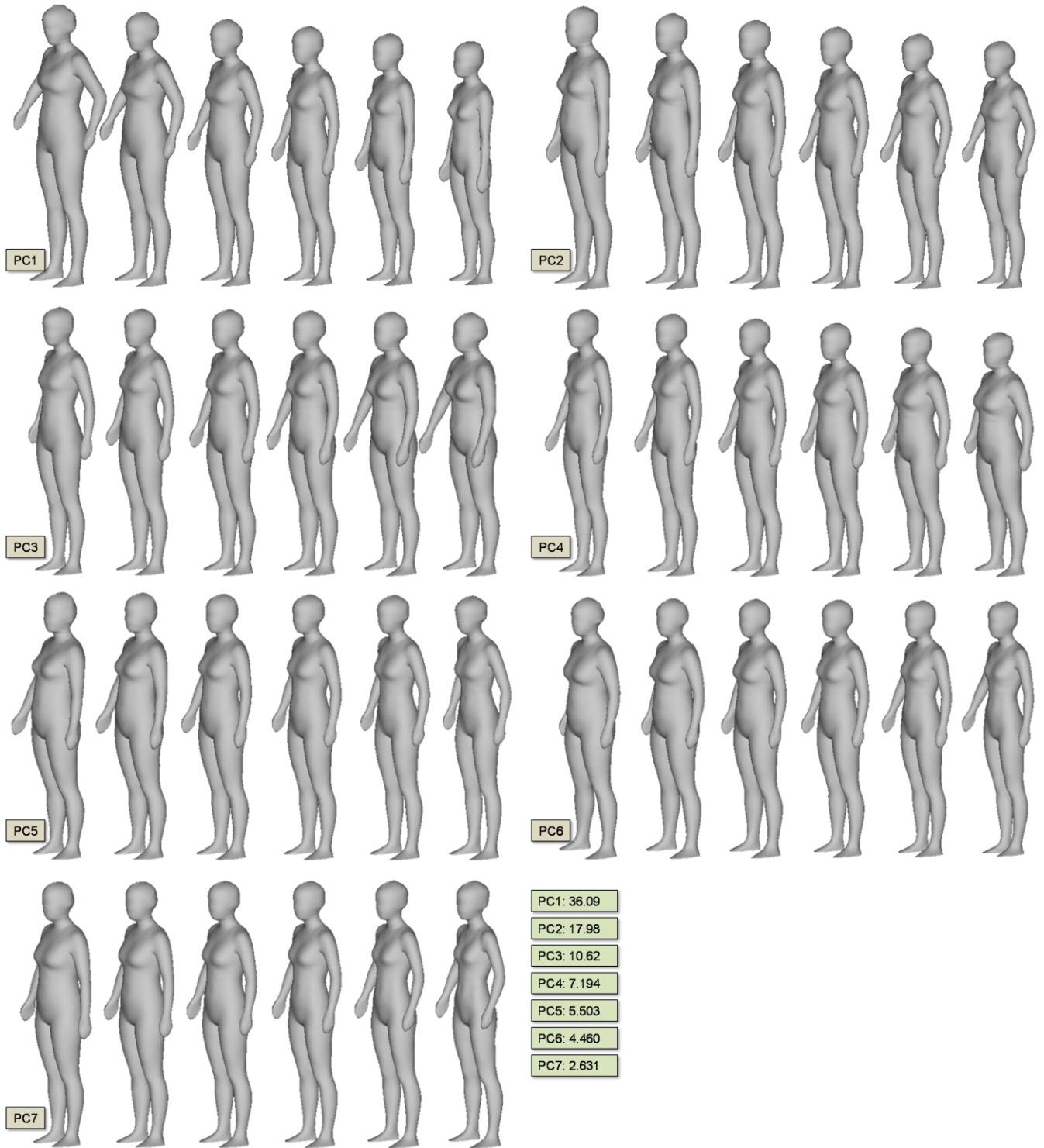


Fig.8. The models spanning the first seven principal components of the female exemplars and their corresponding variances.

illustrated in [14], [15] and [16].

Several topics are worth of pursuing based on this work. First, the feasibility check provides an approximate evaluation for the new parameter values input by the user. Probability (e.g. Bayesian approaches) should be incorporated into the check to enhance its application values. Besides, it is highly advantageous to accelerate generation of the training data. A good method is to integrate image processing techniques with 3D body scanning. The

feature geometry can be automatically extracted from 2D images of a human. Such automatic feature extraction should extend the practicality of semantic parametric design of human body model to a larger extent.

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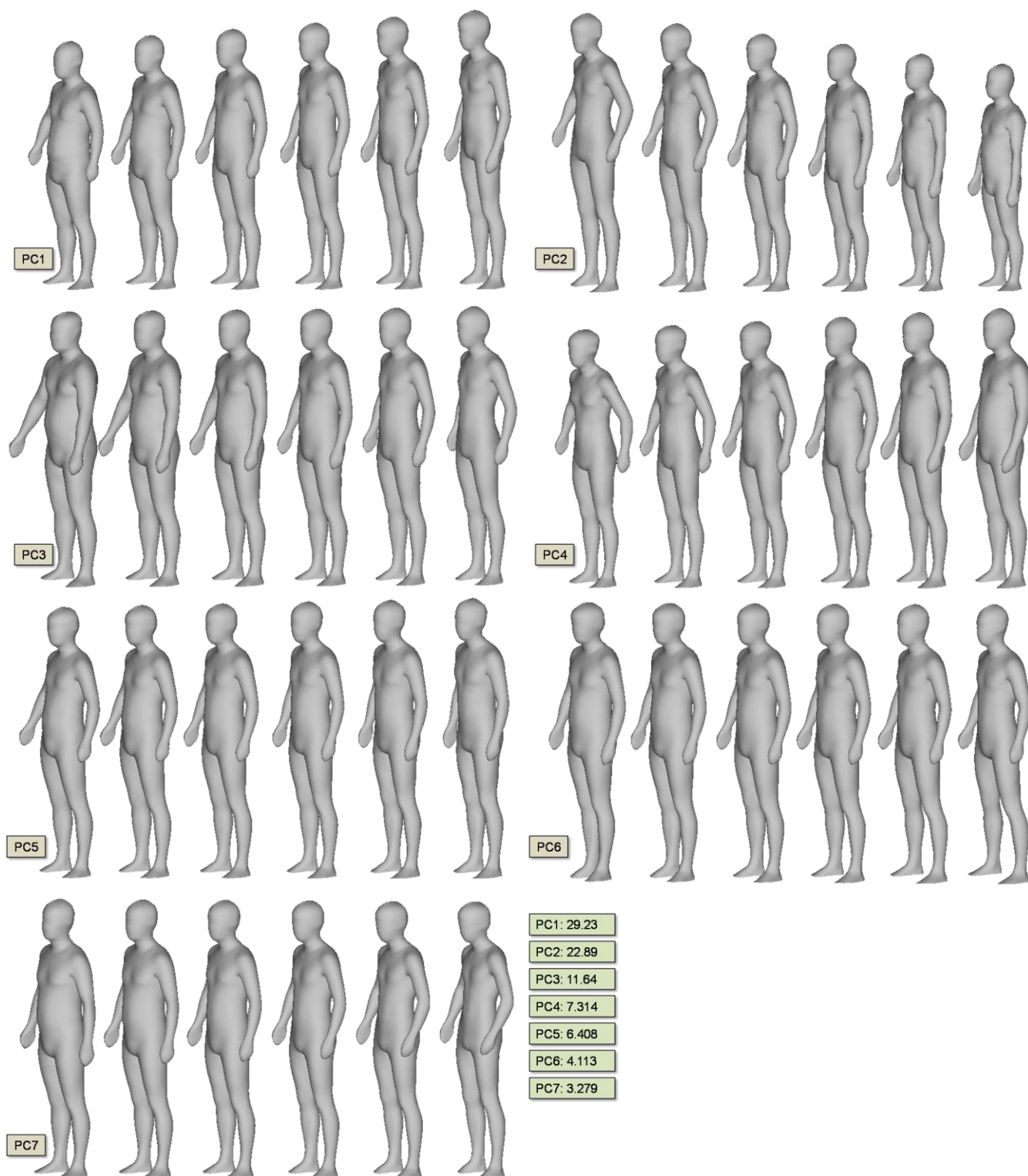


Fig.9. The models spanning the first seven principal components of the male exemplars and their corresponding variances.

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